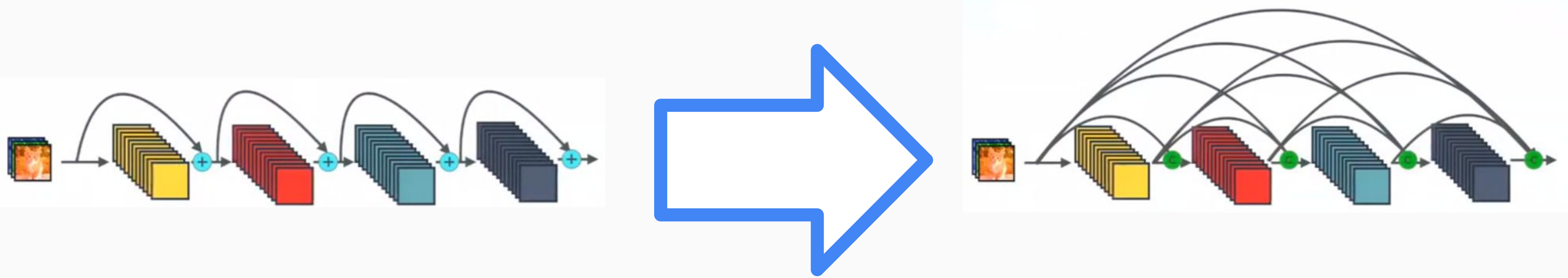
← Speaker: Rodrigo Benenson

Human-in-the-loop annotations

KEEP
CALM
AND
WRITE DOWN
QUESTIONS

Typical machine learning paper focus on model training

Architecture



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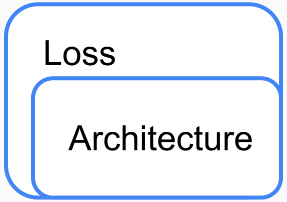

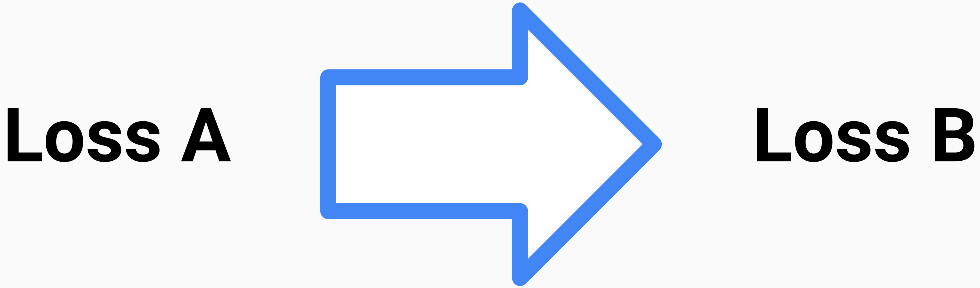

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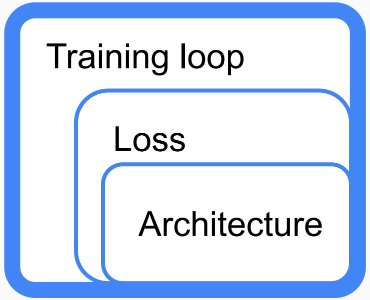
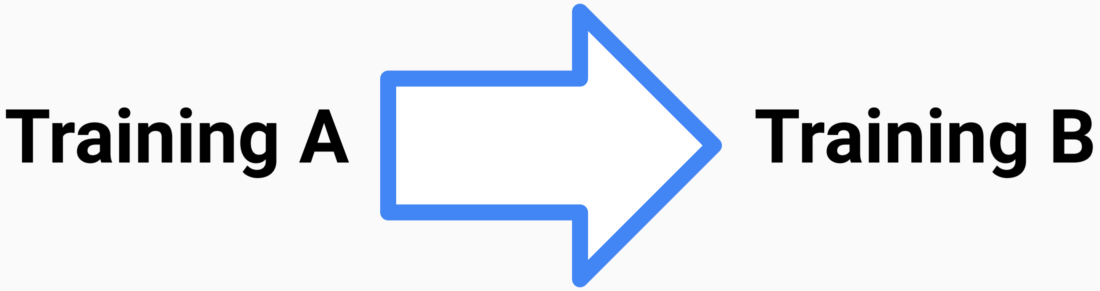
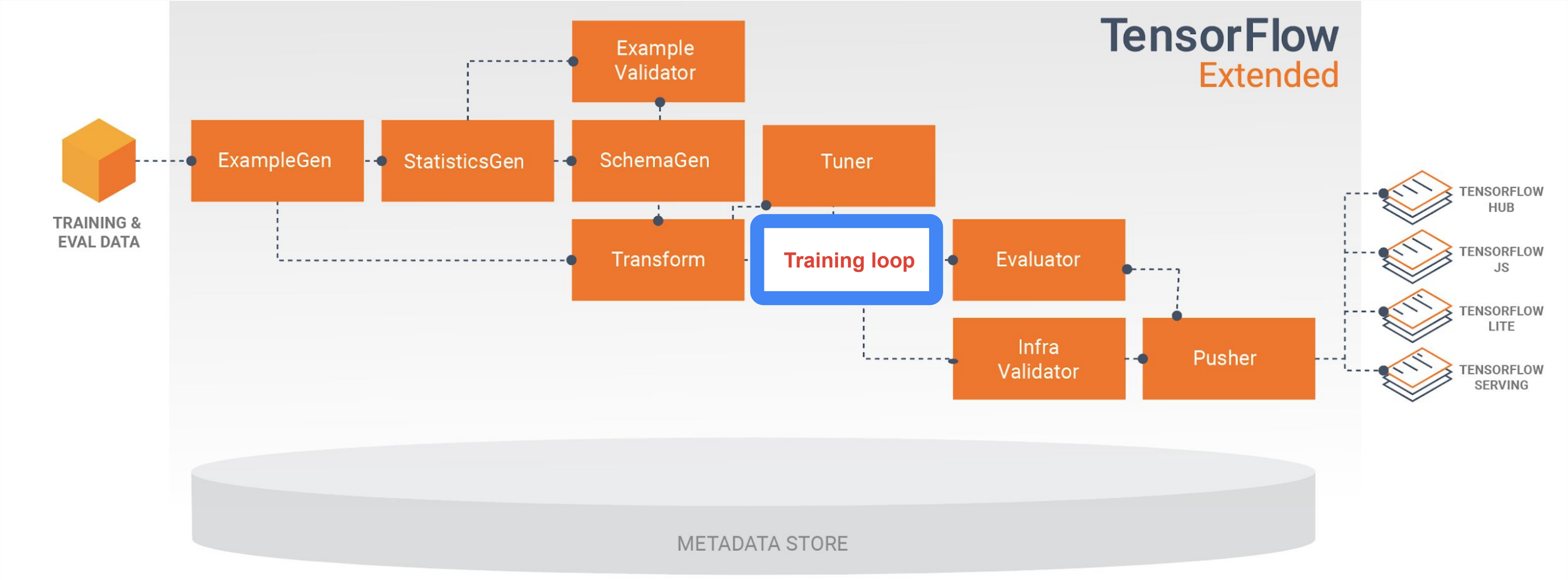
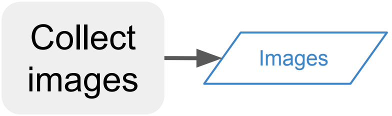




In practice machine learning is much more than data + model



Data collection pipeline



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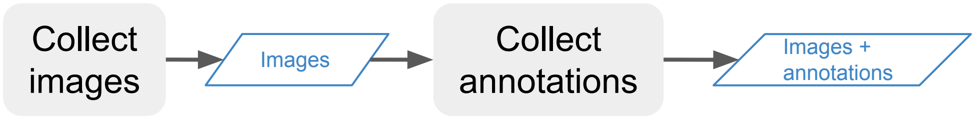

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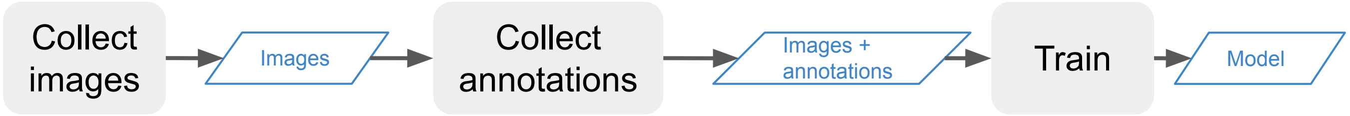

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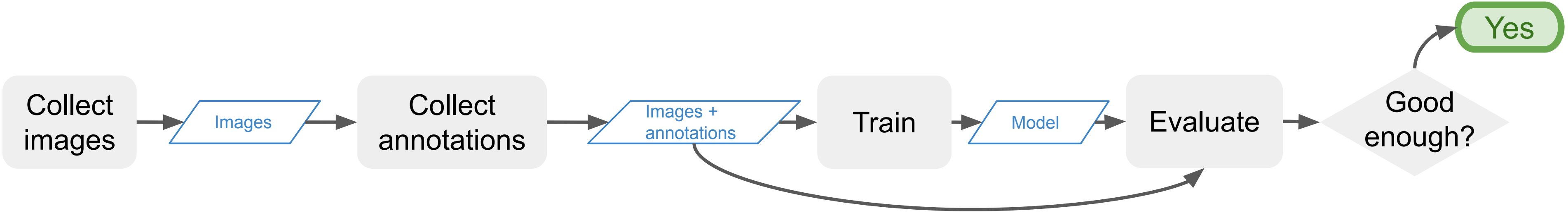

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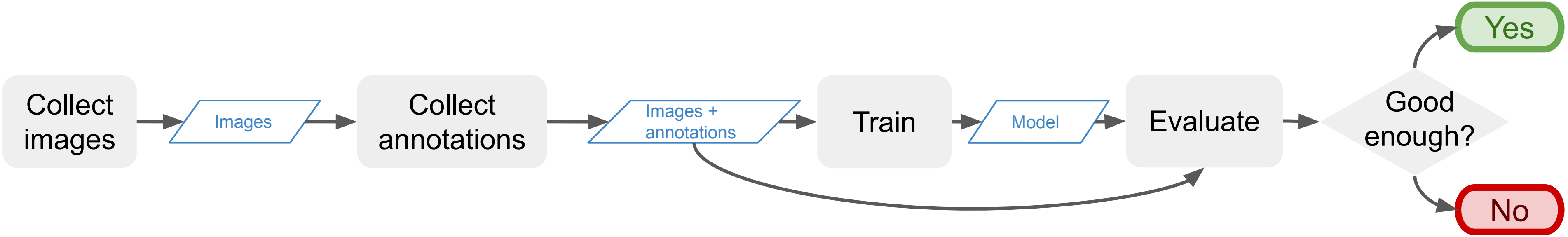

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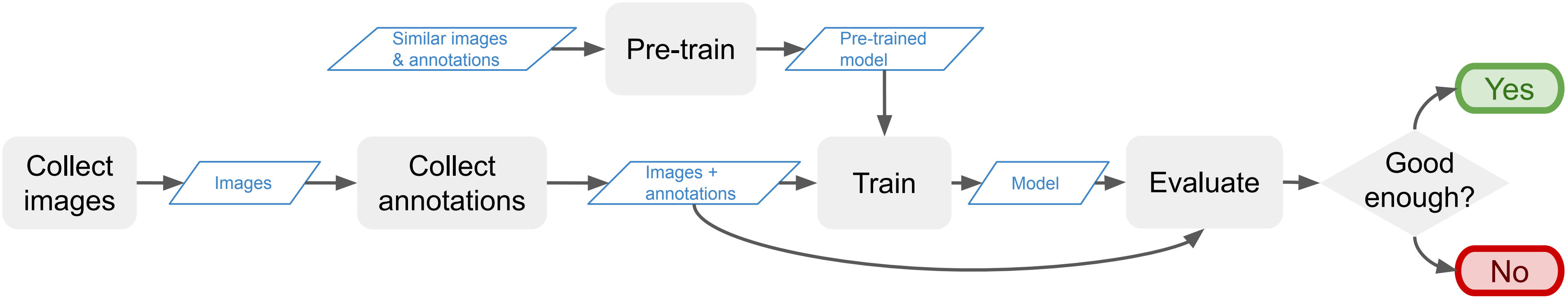
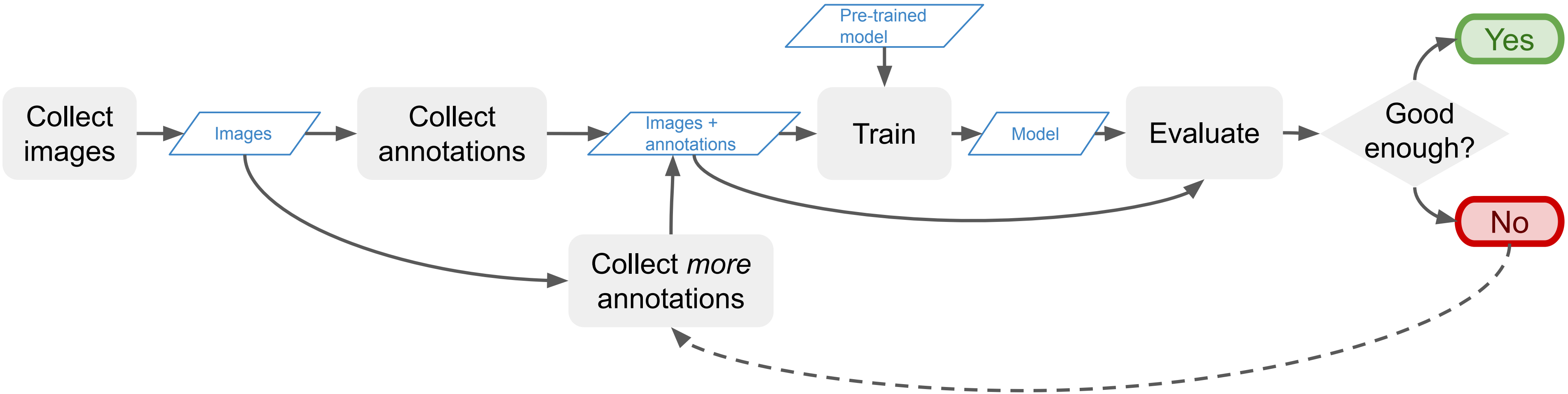


(In practice, transfer learning can be shockingly effective)

Data collection pipeline



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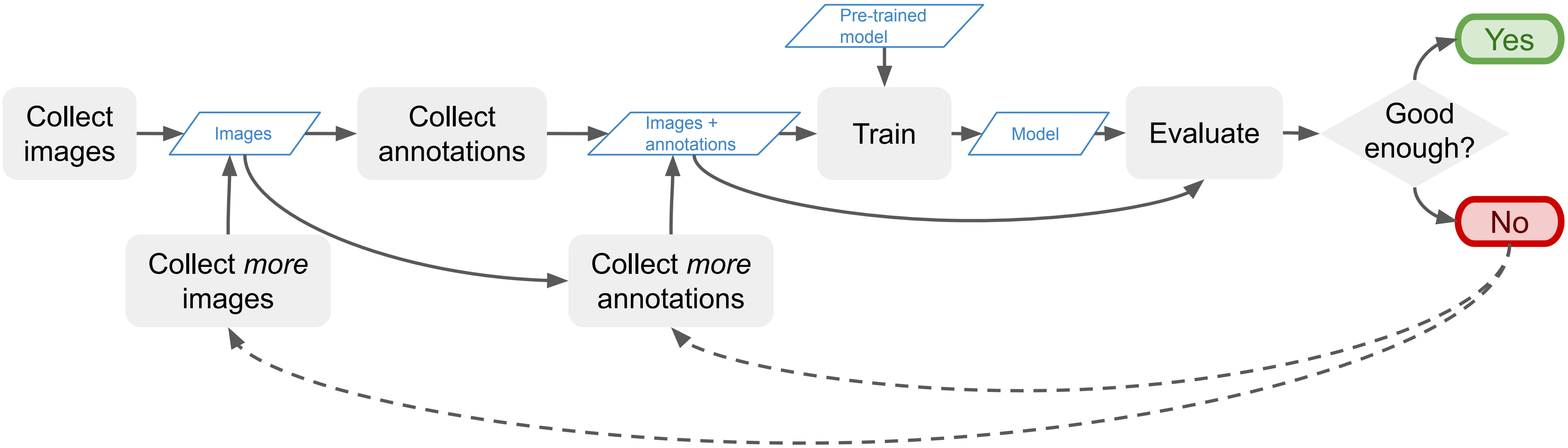

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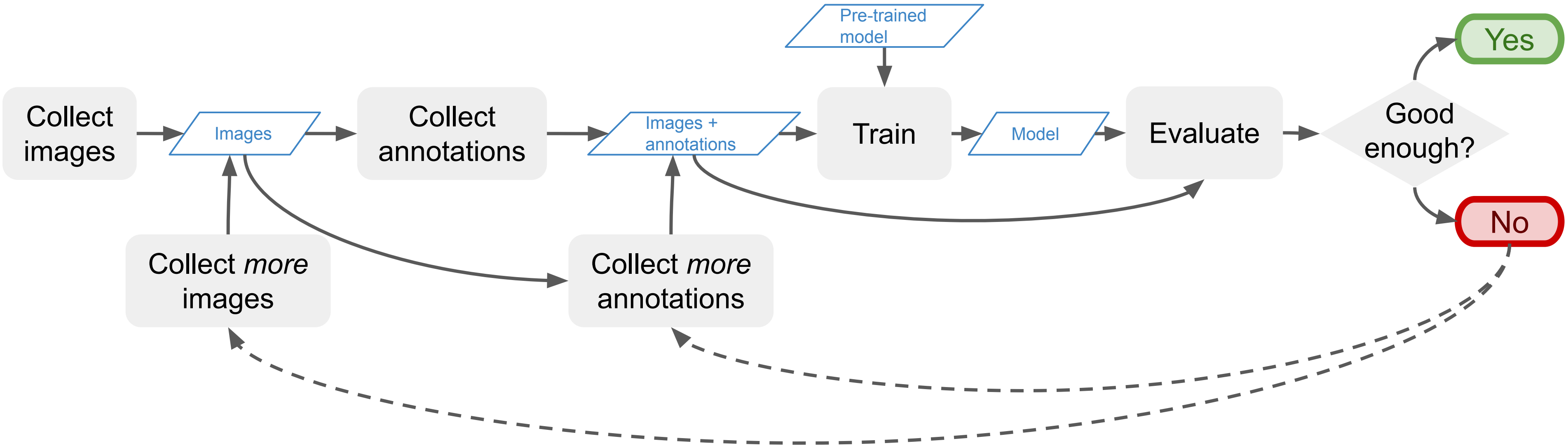

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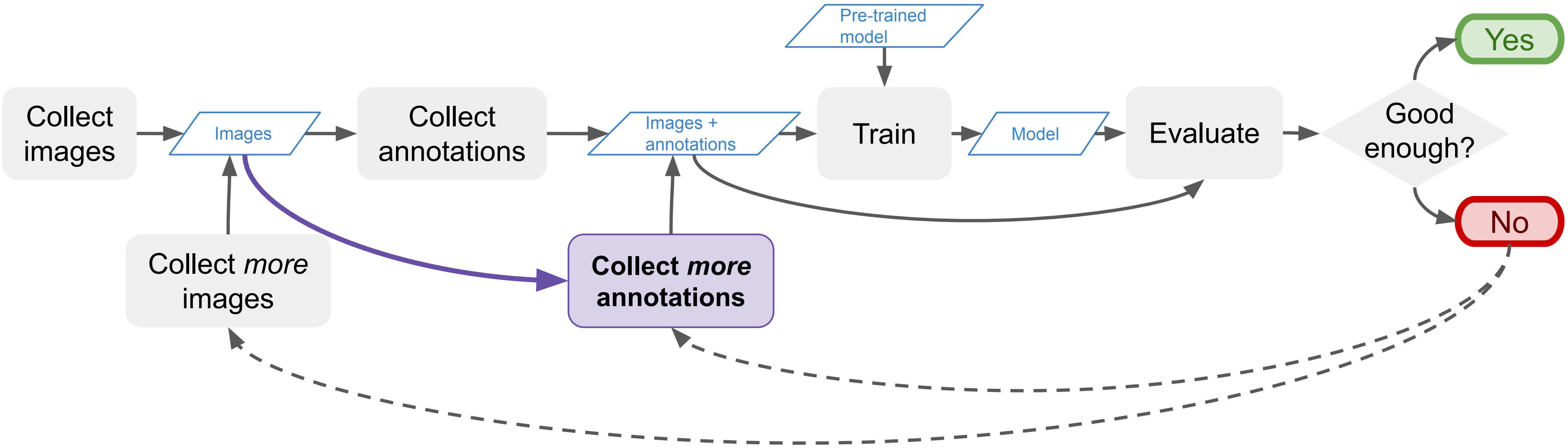
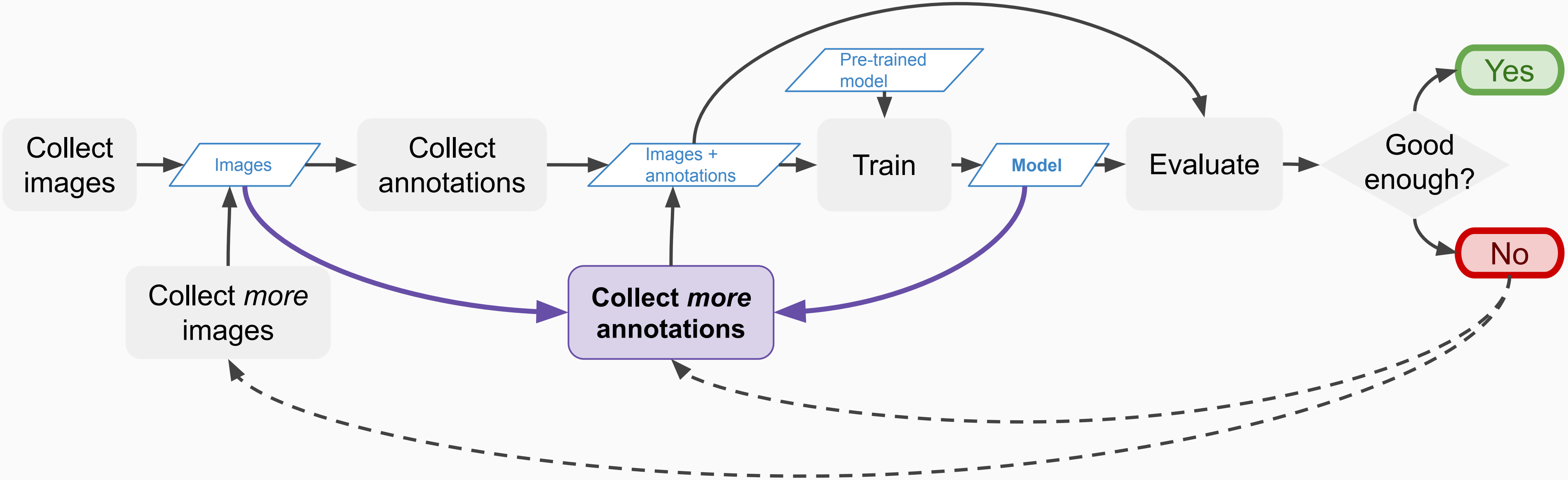


The new annotations should be aware of the model



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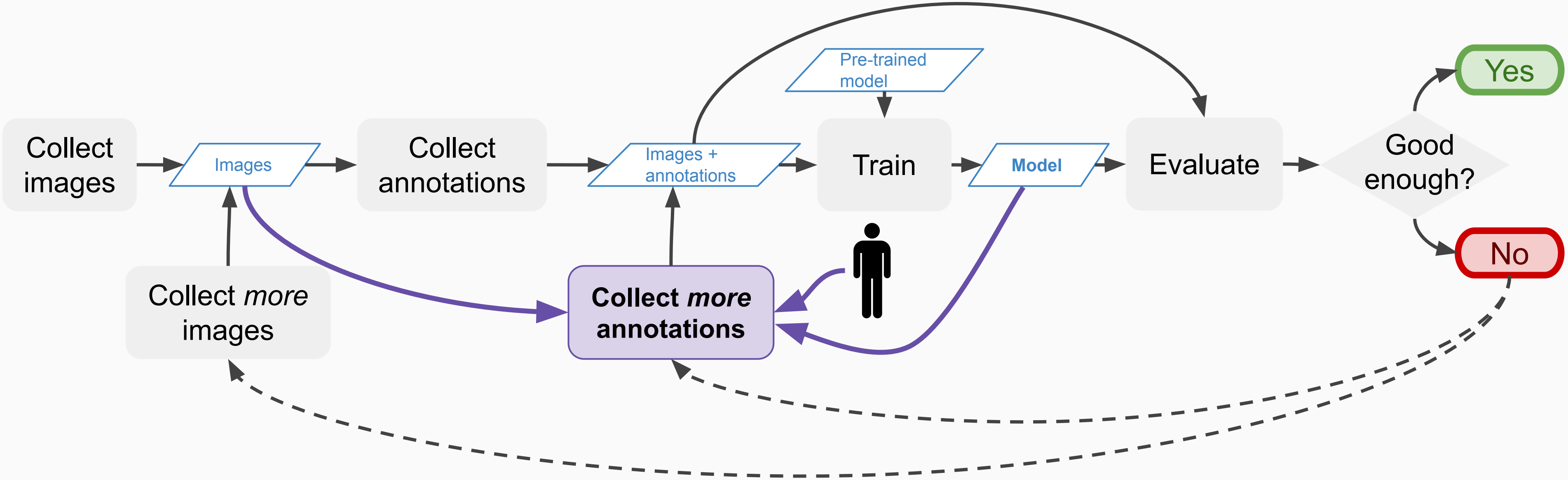

The new annotations should be aware of the model

Before

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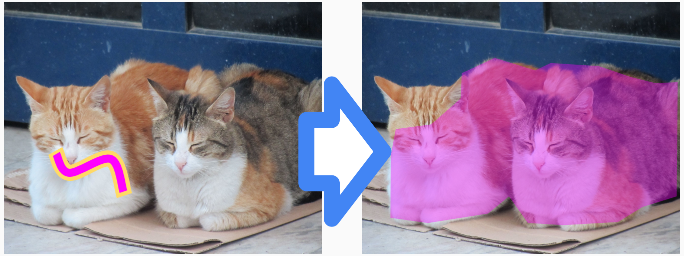
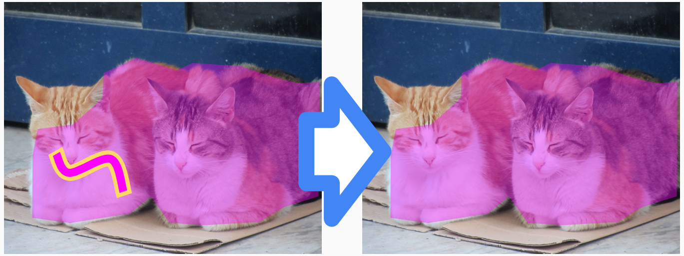
Before After



The new annotations should be aware of the model

Before After



✗Redundant with what the model already knew.

The new annotations should be aware of the model

Before

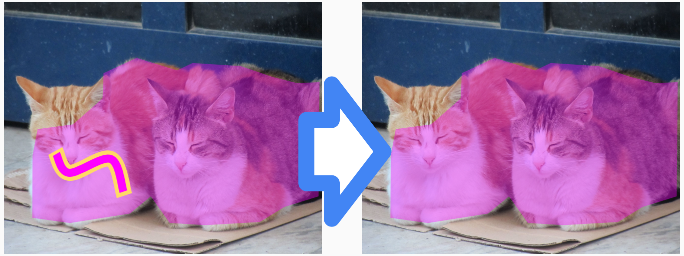
After

✗ Redundant with what the model already knew.

Before

The new annotations should be aware of the model

Before After



✗ Redundant with what the model already knew.

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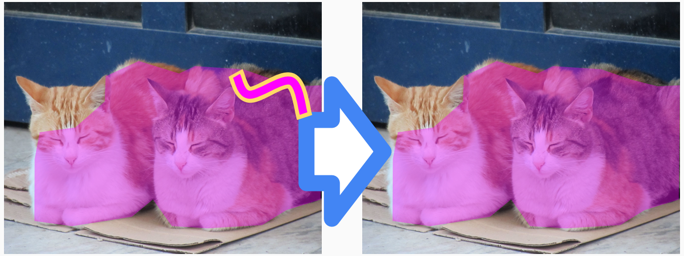
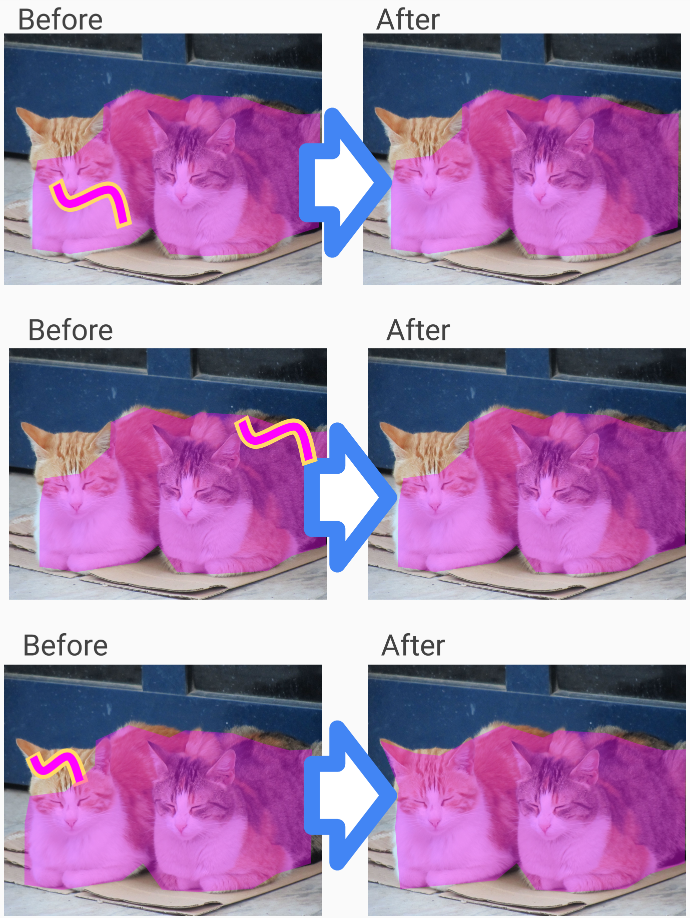


✗ Too hard for the model to learn.

The new annotations should be aware of the model

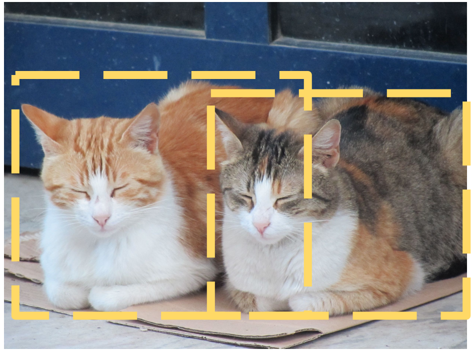


✗ Redundant with what the model already knew.

✗ Too hard for the model to learn.

✓ **Informative** and **learnable** annotation.

Detection



Which boxes to add?

Semantic labeling

Which pixels to add?

Which image areas should be annotated ?

(aka active learning)

Which annotation
will lead to an improved model ?

Which annotation
will lead to an improved model ?

⇒ Hard problem

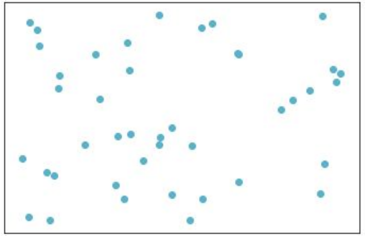
Which annotation
will lead to an improved model ?

⇒ Hard problem

Heuristics

Annotation selection heuristics

- **Uniform**
- Score bands
- High entropy
- Ensemble disagreements
- Self-consistency



Uniform: accept one's ignorance.

Pros:

- As simple as it gets.
- Reasonable strategy to bootstrap annotations.

Cons:

- If model is reasonably good,
  high portion of redundant annotations.
- If class distribution is skewed,
  will under-represent some classes.

Variant (if image-level labels):
uniform annotations,
but only across the bottom-N worst classes.

Annotation selection heuristics

- Uniform
- **Score bands**
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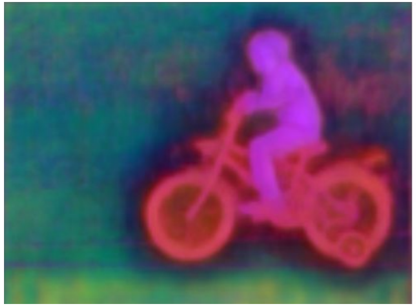

Score band: focus on areas with score ∈ [a, b].

E.g. score ∈ [0.4, 0.6], score ∈ [0.8, 0.9].

Pros:
- Simple to implement.
- Can easily target ambiguous regions.
- Can aim for class-balanced sampling.

Cons:
- Empirically not very effective.

Annotation selection heuristics

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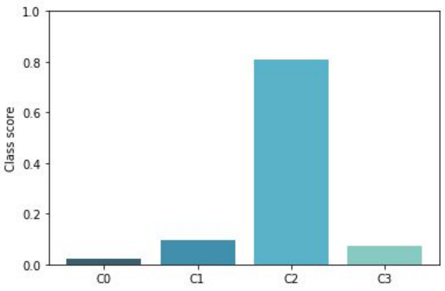
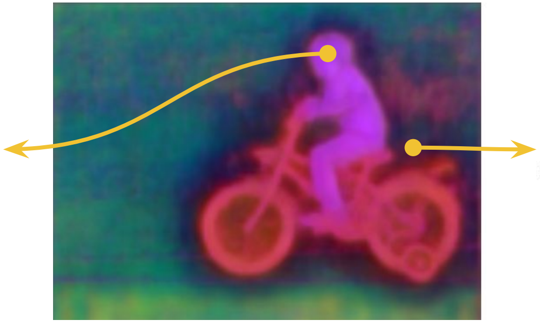
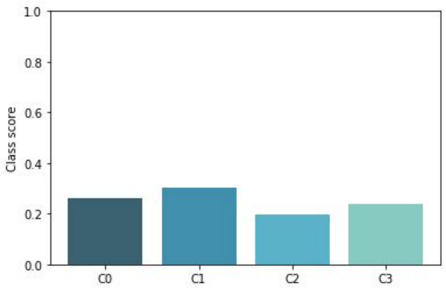


Low confusion





High confusion

High entropy: focus on areas of model confusion.

$$H(x) = -\sum_k p_k \log(p_k)$$

Pros:

- Simple to understand.
- Annotated samples guaranteed to provide training loss.
- Empirically hard to beat.

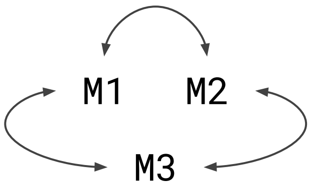
Cons:

- Does not include a notion of sample diversity.

Annotation selection heuristics

- Uniform
- Score bands
- High entropy
- **Ensemble disagreements**
- Self-consistency

Ensemble disagreements:
focus where N models disagree.



Disagreement measured by l2-norm,
Jensen-Shannon divergence, vote entropy, etc.

Pros:
- Better estimation of model uncertainty.
- Provides better results than single model.

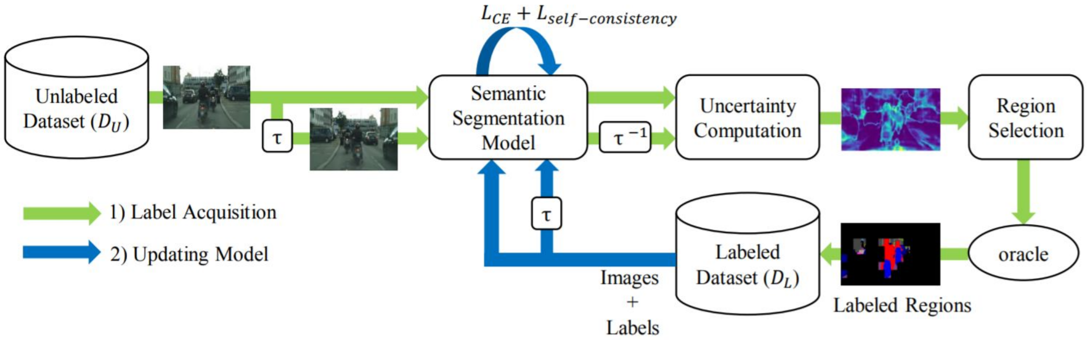
Cons:
- Requires training multiple models.
  (Ensemble can be approximated via dropout)

(Ensemble average can also be used as a single stronger model, and use high-entropy)

[Dagan & Engelson ICML 95]

Annotation selection heuristics

- Uniform
- Score bands
- High entropy
- Ensemble disagreements
- **Self-consistency**



Self-consistency:
focus where equivariance is not respected.

Pros:
- Simple to understand.
- Can (should) be combined with the previous heuristics.

Cons:
- (Requires hand-crafting the test-time augmentation).

[Golestaneh & Kitani arxiv 2020]

Opinion: active learning is a field where most ideas do not work.

(most ideas work a little, sometimes)

If in doubt: ensemble model + entropy + self-consistency.

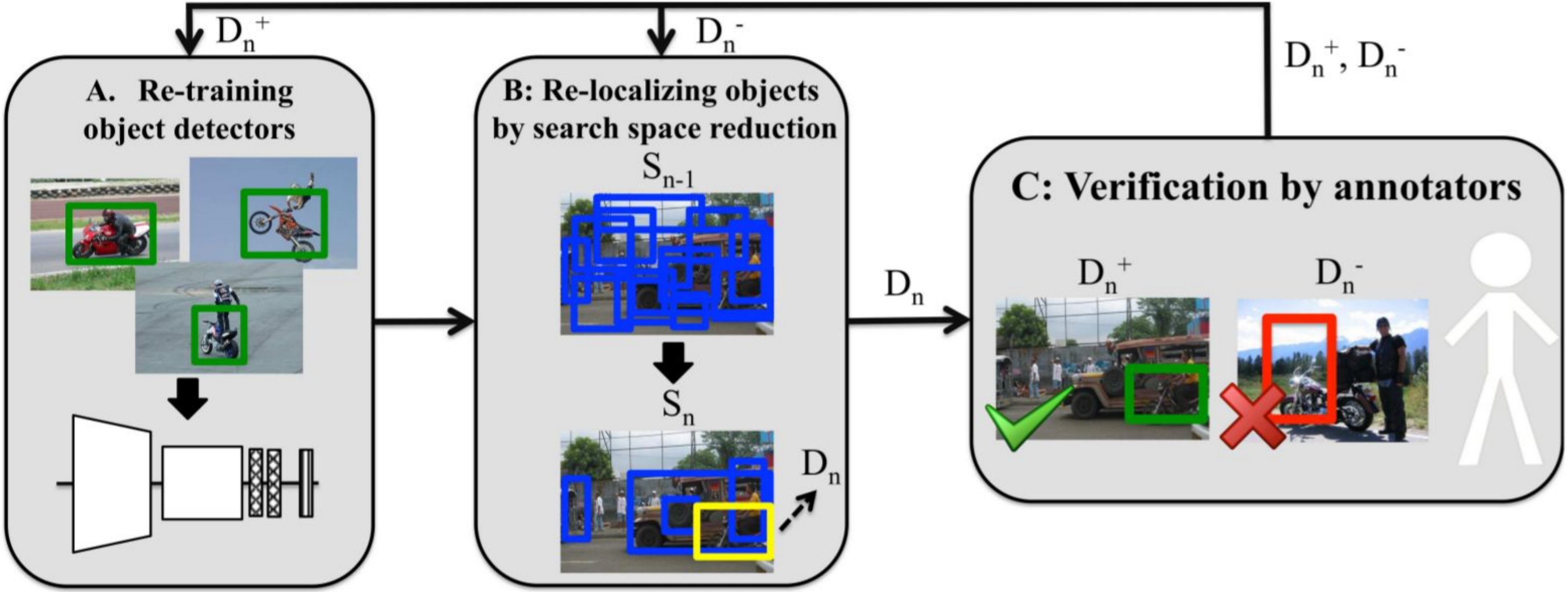
[BALD, LAL, RALIS, CEREALS]

Collecting bounding boxes

(without drawing any box)

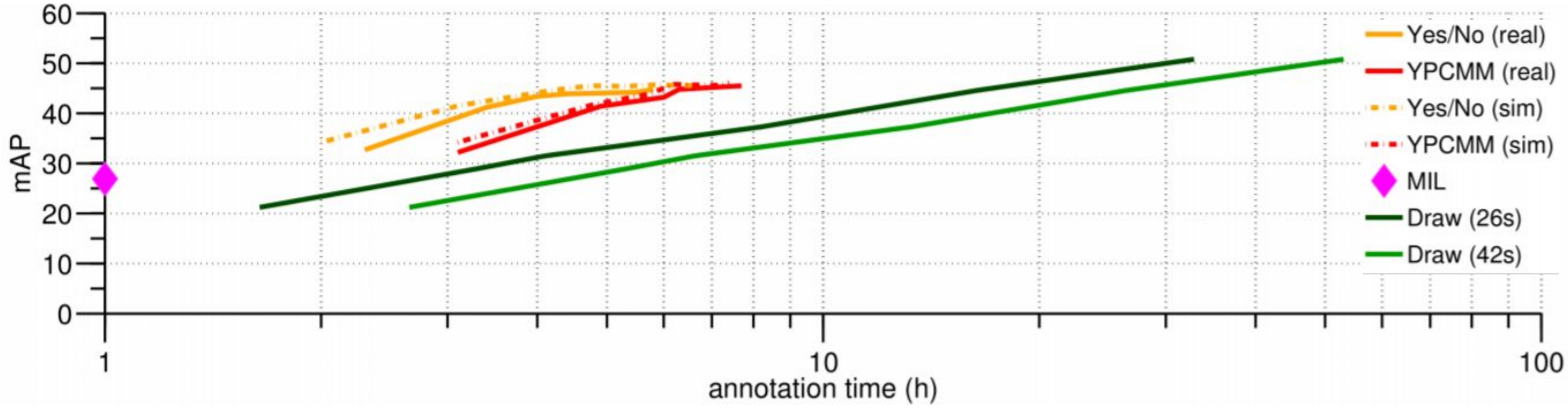
The annotator verifies boxes instead of drawing them

(yes/no or yes/part/container/mixed/missed)



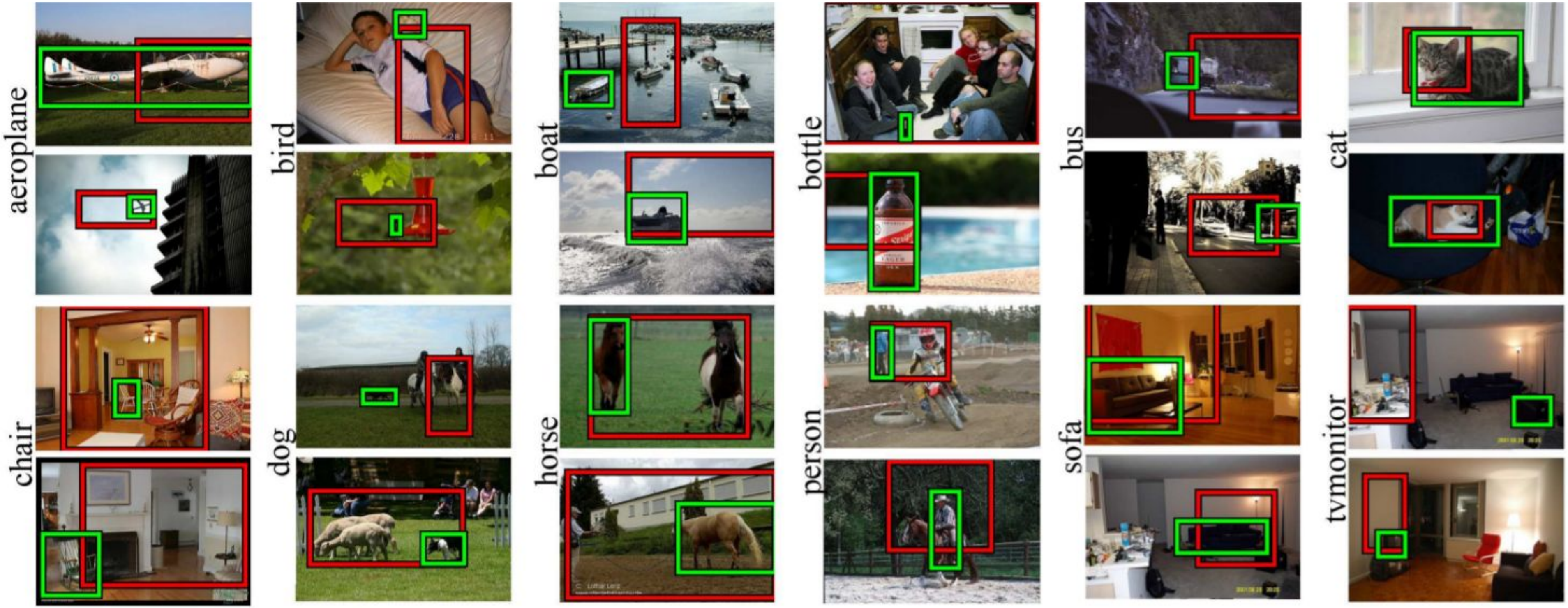
[Papadopoulos et al. CVPR 2016]

Better model when limited human time budget



Pascal VOC 2007 object detection evaluation.

[Papadopoulos et al. CVPR 2016]



Red: weakly supervised bounding boxes (from image-level labels).
Green: boxes after collecting verifications.

[Papadopoulos et al. CVPR 2016,
see also Kao ACCV 2018, Pardo et al. arxiv 2019]

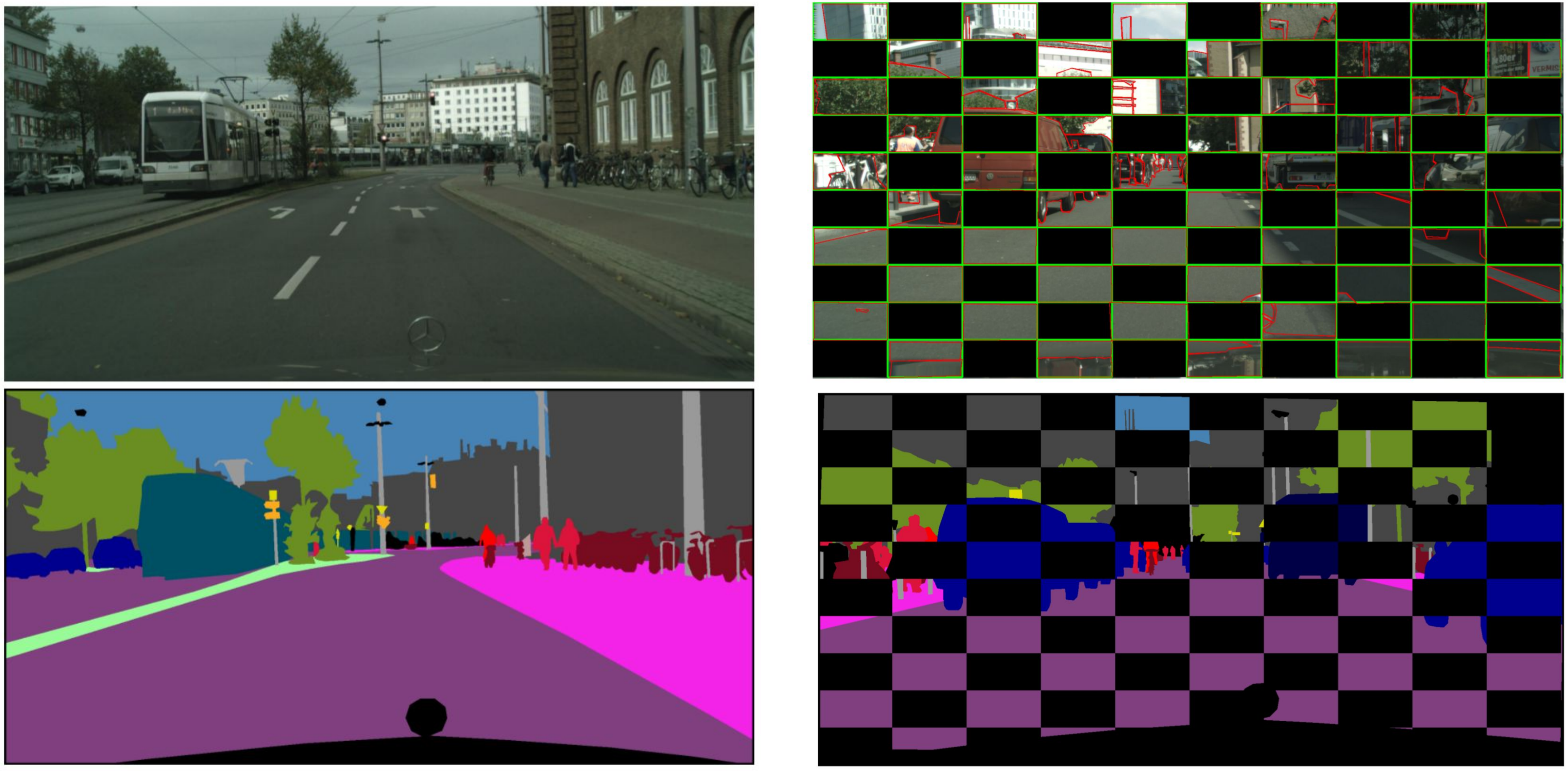
Collecting segmentations

(guiding the drawing hand)

Segmentation annotations do not need to be complete

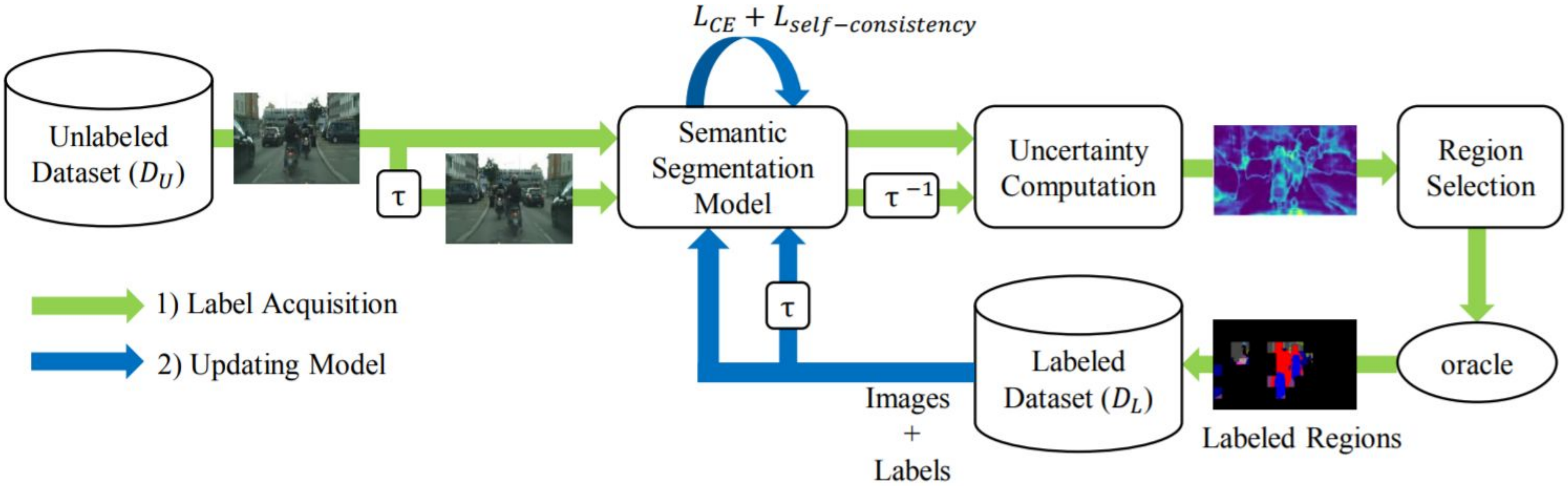
[Lin et al. ICCV 2019]

Segmentation annotations do not need to be complete



[Lin et al. ICCV 2019]

Segmentation blocks can be machine-selected



[Golestaneh & Kitani arxiv 2020]

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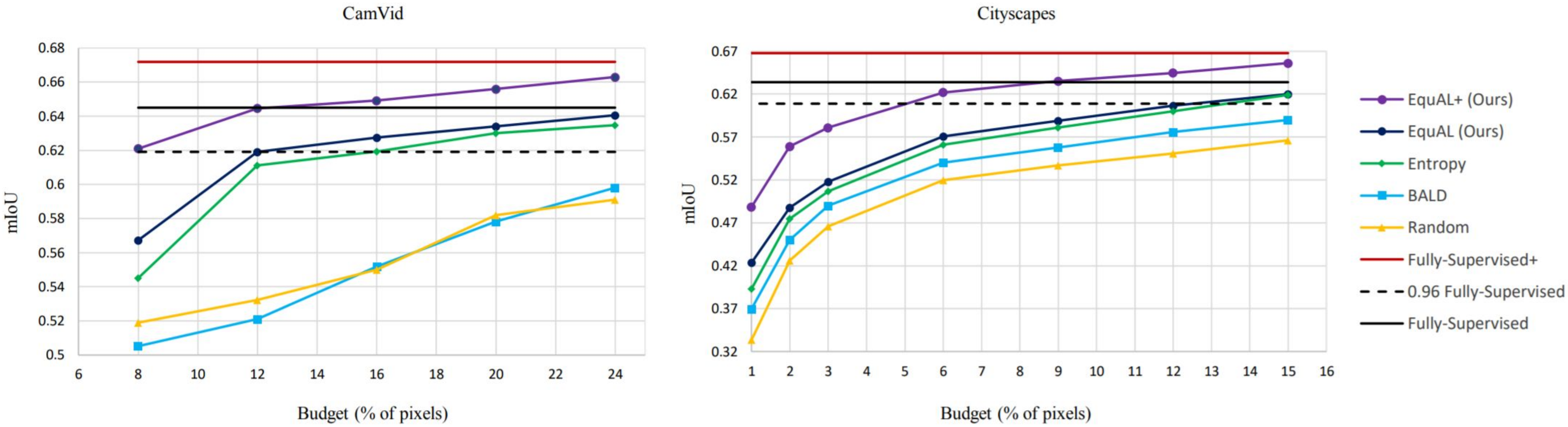

[Golestaneh & Kitani arxiv 2020]

Collecting segmentations

(guiding the clicking hand)

Focusing user actions to errors

(per instance, masks corrective clicks)

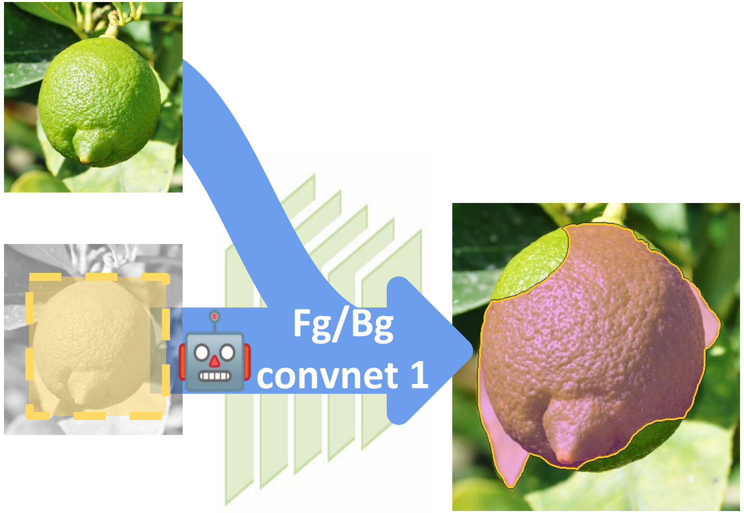

Image + Mask

[Benenson et al. CVPR 2019]

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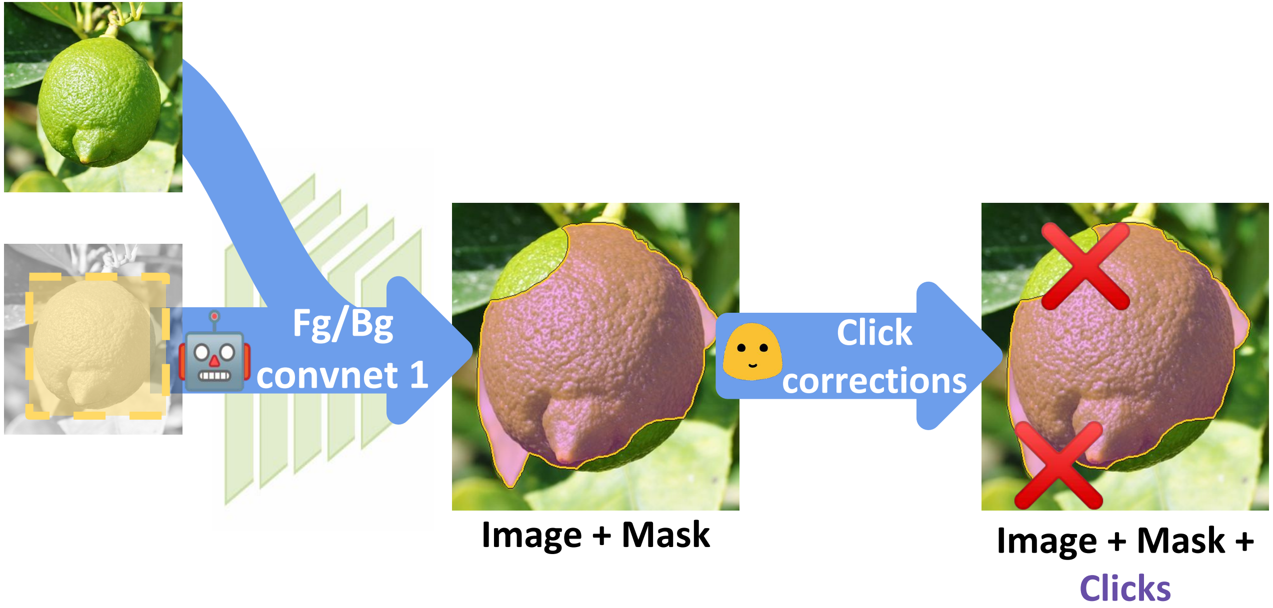

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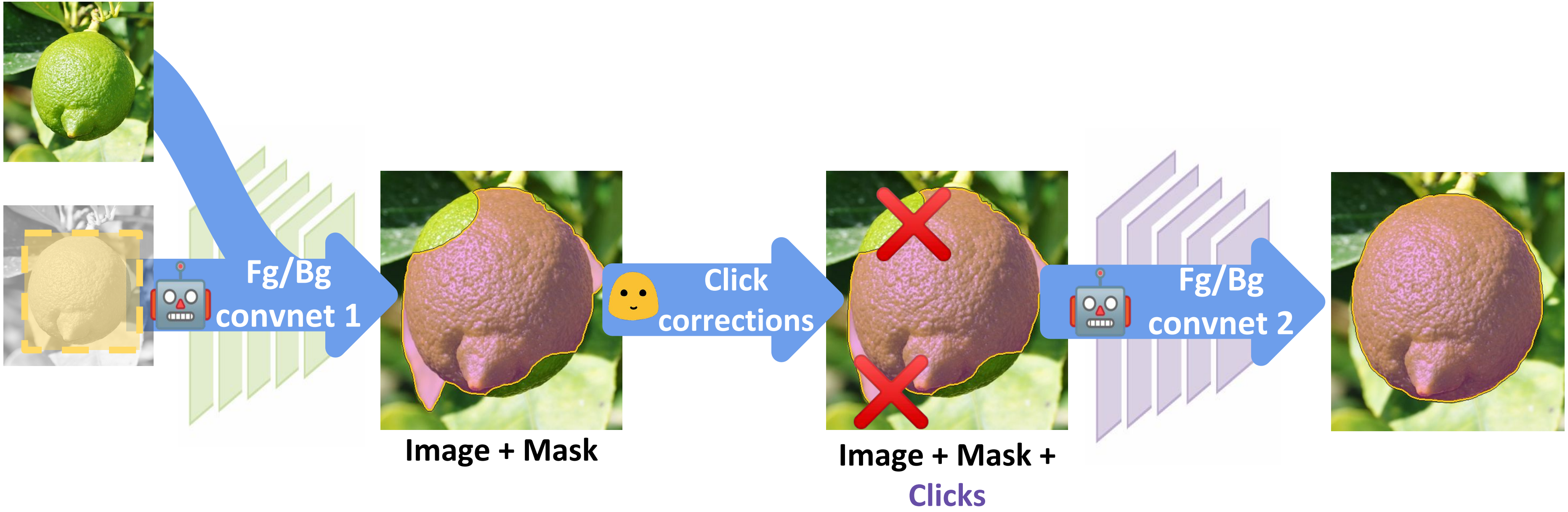

[Benenson et al. CVPR 2019]

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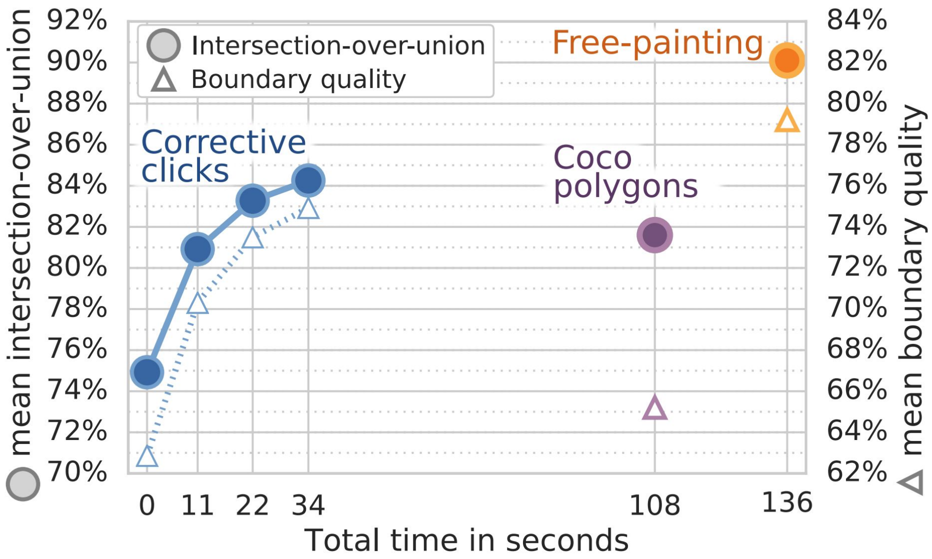
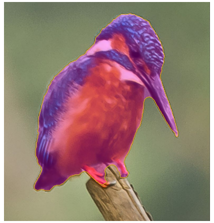


- Quality > COCO polygons
- ~3x faster annotation time
- 2.5M instances masks

https://g.co/dataset/open-images

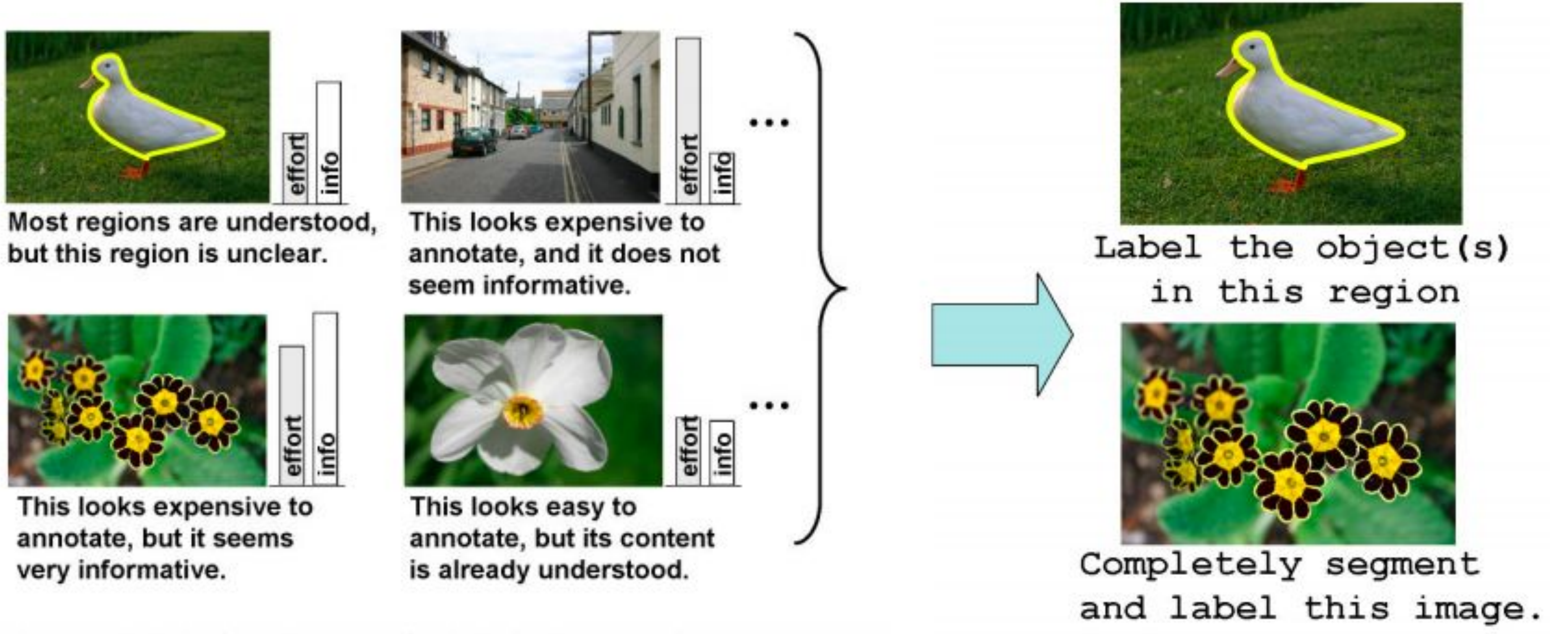



[Benenson et al. CVPR 2019, Kontogianni et al. ECCV 2020]

Annotation dialogs

(where the machine ask)

The best strategy covers different annotation types, the machine asks what it needs.



[Vijayanarasimhan and Grauman CVPR 09, Russakovsky et al. CVPR 15, Konyushkova et al. CVPR 18]

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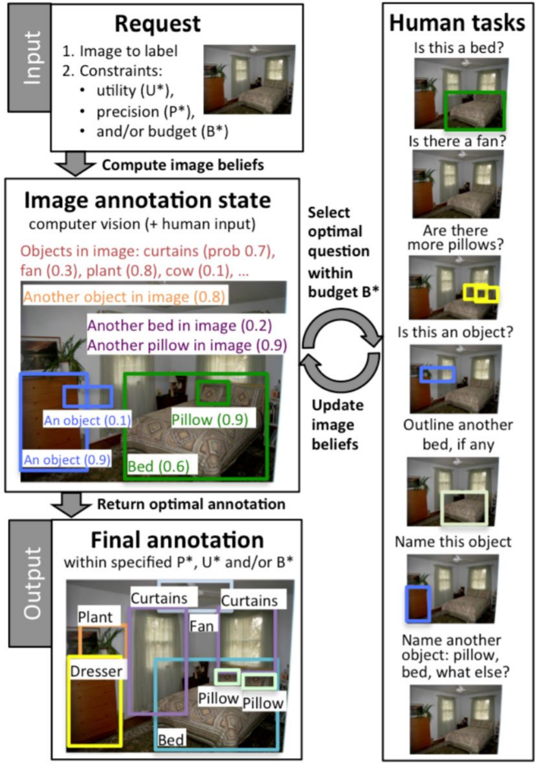

[Vijayanarasimhan and Grauman CVPR 09, Russakovsky et al. CVPR 15, Konyushkova et al. CVPR 18]

Takeaways:

- For large scale annotation campaigns,
  hybrid annotations enable better use of human time.
- Strong annotations can be partial, and focused.
- For active learning component, keep it simple.
- Do not underestimate the power of transfer learning.
- There is a large design space for Human-Machine collaboration.

?